

Discovery of Evolving Semantics through Dynamic Word Embedding Learning

Zijun Yao*
Rutgers University
zijun.yao@rutgers.edu

Yifan Sun
Technicolor Research
yifan.sun@technicolor.com

Weicong Ding
Technicolor Research
dingwc@bu.edu

Nikhil Rao
Technicolor Research
nikhil.rao@technicolor.com

Hui Xiong
Rutgers University
hxiong@rutgers.edu

ABSTRACT

During the course of human language evolution, the semantic meanings of words keep evolving with time. The understanding of evolving semantics enables us to capture the true meaning of the words in different usage contexts, and thus is critical for various applications, such as machine translation. While it is naturally promising to study word semantics in a time-aware manner, traditional methods to learn word vector representation do not adequately capture the change over time. To this end, in this paper, we aim at learning time-aware vector representation of words through dynamic word embedding modeling. Specifically, we first propose a method that captures time-specific semantics and across-time alignment simultaneously in a way that is robust to data sparsity. Then, we solve the resulting optimization problem using a scalable coordinate descent method. Finally, we perform the empirical study on New York Times data to learn the temporal embeddings and develop multiple evaluations that illustrate the semantic evolution of words, discovered from news media. Moreover, our qualitative and quantitative tests indicate that the our method not only reliably captures the semantic evolution over time, but also consistently outperforms state-of-the-art temporal embedding approaches on both semantic accuracy and alignment quality.

KEYWORDS

Word Embedding, Dynamic

1 INTRODUCTION

Human language is an evolving construct. Words change their meanings over time, with new concepts and phenomena developing and old ones dying. For example, the word *gay* traditionally meant happy, but today it is more commonly associated with one's sexual orientation. Names of celebrities or brands, in particular, are constantly changing their association. For example, until very recently, *trump* was not identified as a politician but a real estate developer. Also, *apple* which was recognized as a computer company originally in early 90s, has transitioned into a smartphone company because of the recent success of the iPhone. Meanwhile, completely new words like *obamacare* and *mansplain* emerge suddenly, with once-significant terms like *scabs* and *hooligans* falling out of use.

Although these semantic changes pose significant challenges in natural language processing when dealing with highly evolving corpora, especially newspapers and blogs, it can be a great asset

for understanding the dynamics of human language if temporal evolution of the word can be mathematically captured. While previous literature has recognized the significant effects of temporality in text processing, such as temporal topic modeling [5, 29, 30], relatively little attention has been given to using dynamic *word embeddings* to track the evolving media. Word embeddings are vector representations of words, placed such that words with similar meanings are geometrically close. (e.g. *red* and *blue* are closer than *red* and *squirrel*.) Classic word embedding techniques date back to the 90s, relying on statistical approaches [7, 18] or neural networks [4], with notable recent advances such as GloVe [24] and word2vec [21, 22] which have been shown to greatly improve the performance of natural language tasks. However, these methods assume a single state for each word across all time, making it incapable for handling semantic evolution.

Motivated by the above discussion, we are interested in computing *temporal* word embeddings; that is, words in different time frames (e.g., years) are represented by different vectors. Dynamic word embeddings are better able to capture the evolution of human language. For example, the trajectory of the public perception of celebrities or brands can be visualized by tracking neighboring words across times. For example *trump* has a trajectory of *estate* → *television* → *republican*. In another example, emerging words (e.g., *mp3*) which did not exist before, can be automatically analyzed by inferring its precedent words (e.g., *stereo*).

In practice, two unique challenges arise in learning temporal word embeddings: i) Splitting the corpus by time makes the data extremely sparse, since the observation of word-word co-occurrences are now distributed across times. In worse cases, some words can be completely missing in some time slices. ii) To be able to compare embeddings across time for evolution tracking, they should be expressed in a single coordinate space. This leads to an alignment problem which though previously addressed, is still a challenge.

Unlike traditional word embeddings, the literature on learning temporal word embeddings is relatively short: [10, 13, 17, 34]. The approaches in these works follow a similar pattern: first, compute static word embeddings in each time slice separately, then find a way to align the word embeddings across time slices. To achieve alignment, [13] finds a linear transformation of words between any two time slice by solving a d -dimensional least squares problem of k nearest neighbor words (where d is the embedding dimension). [34] also use the linear transformation approach between a base and target time slices, and computes the linear transformation using anchor words, which do not change meaning between the two time

*This work was done during an internship at Technicolor Research, Los Altos, CA.

slices. [10] imposes the transformation to be orthogonal, and solves a d -dimensional Procrustes problem between every two adjacent time slices.

In this work, our main technical novelty is to compute word embeddings and alignments *jointly*, through solving one overall optimization problem. In face, previous two-step (learning-alignment) solutions optimally learn segments of our model independently, and thus can be viewed as suboptimal solutions of our model. Meanwhile, since jointly computing embeddings for all time slices increases computational needs, we discuss how to implement a block coordinate descent algorithm in a way that maintains computational scalability. There are three main advantages to our joint model approach. First, because our embeddings are algorithmically agnostic, it is theoretically more interpretable. Second, by training all vectors jointly, we share information across time slices for the majority of the static words; for this reason, our method is more robust against data sparsity. Third, as the alignment of embeddings is built into the optimization process and involves embeddings across time slices simultaneously, the quality of alignment is better than post-learning alignments that only consider two time frames' worth embeddings at each alignment phase.

In addition to the embeddings learning model, we provide a framework to evaluate temporal word embeddings from the perspective of evolving semantics discovery. First, we offer a new training corpus of around 100,000 major New York Times articles from 1990 to 2016. In comparison, previous temporal word embedding works have focused on timestamped novels and magazine collections (such as Google N-Gram and COHA). The main advantages of using news corpus are their 1) consistency in spelling and grammar, 2) preference toward using common vocabulary and plain sentence structure over artistic, esoteric flairs, and 3) commitment to report only the most current, relevant topics of the day. Second, we develop both qualitative and quantitative methods to evaluate temporal embeddings; this has traditionally been difficult because of the inherent subjectiveness in evaluating word semantics, and a dearth of labeled data. Qualitatively, we illustrate the advantages of temporal embeddings for evolving semantics discovery by 1) looking at norms as a representative of concept popularity, 2) plotting word vector trajectories to find evolving meanings and associations, and 3) using alignment through time to identify similar roles across time. Quantitatively, we first use semantic similarity extracted from section information (e.g., *Technology*, *World*) of news articles as groundtruth to evaluate the semantic accuracy of temporal embedding. Secondly, we provide two testsets to evaluate cross-time alignment quality; one consists of known changing roles (e.g., U.S. presidents), determined objectively, and one of concept replacements (e.g., disk to mp3), determined subjectively. These testsets can be used to evaluate temporal embeddings in general.

In summary, the contributions of this work are as follows:

- We present a unified dynamic model which incorporates embedding alignment among different time slices into the embedding learning process. Our model provides accurate word embedding, with high quality cross-time alignment, and is robust to data sparsity.
- We develop a scalable block coordinate descent based algorithm to train the proposed dynamic embedding model efficiently.

- We implement our proposed model on New York Times articles across 27 years. By visualizing the embeddings, we find interesting insights to semantic evaluations. Lastly, we develop quantitative tests for evaluating our temporal word embeddings against state-of-the-art baselines.

The rest of this paper is organized as follows. In section 2, we present the proposed model for temporal embedding learning, and in section 3, we describe a scalable algorithm to train it. Section 4 describes the news corpus dataset and setup details of experiments. Section 5 uses the word embeddings to track interesting phenomena in the news. Finally, in section 6, we compare our embedding against other state-of-the-art temporal embeddings in two aspects: semantic similarity, and alignment quality.

2 METHODOLOGY

We now set up our temporal word embedding model. We consider a text corpus collected across time. These kinds of corpora such as news article collections with published dates or social media discussion with time-stamps are ubiquitous. Formally, we denote by $\mathcal{D} = (\mathcal{D}_1, \dots, \mathcal{D}_T)$ our text corpus where each \mathcal{D}_t , $t = 1, \dots, T$, is the corpus of all documents in the t -th time slice. Without loss of generality, we assume the time slices are ordered chronologically. The length of these time slices can be months, years, or decades. Moreover, the length of all the time slices could be different. We consider an overall vocabulary $\mathcal{V} = \{w_1, \dots, w_V\}$ of size V . We note that the vocabulary \mathcal{V} consists of words happening at any point in time, and thus it is possible for some $w \in \mathcal{V}$ to not appear at all in some \mathcal{D}_t . This includes emerging words and dying words that are typical in real-world news corpora.

Given such time-tagged corpus, our **goal** is to find a dense, low-dimensional representation vector $u_w(t) \in \mathbb{R}^d$, $d \ll V$ for each word $w \in \mathcal{V}$ and each time period $t = 1, \dots, T$. We denote by u_w the static embedding for word w , and d is the embedding dimension (typically $50 \leq d \leq 200$). Compactly, we denote by $U(t)$ (of size $V \times d$) the embedding matrix of all words whose i -th row corresponds to the embedding vector of i -th word $u_{w_i}(t)$.

2.1 Time-agnostic word embeddings

A fundamental observation in static word embedding literature is that semantically similar words often appear as neighbors in a corpus [8]. This is the idea behind learning dense low-dimensional word representations both traditionally [4, 7, 18] and recently [21, 24]. In several of these methods, the neighboring structure is captured by the frequencies of which pairs of words cooccur within a small local window. In this paper we adopt the approach of word2vec [21] and GloVE [24] and our embedding is also based on the same local co-occurrence structure.

Formally, we compute the $V \times V$ pairwise mutual information (PMI) matrix specific to a corpus \mathcal{D} , whose w, c -th entry is:

$$\text{PMI}(\mathcal{D}, L)_{w,c} = \log \left(\frac{\#(w, c) \cdot |\mathcal{D}|}{\#(w) \cdot \#(c)} \right) \quad (1)$$

where $\#(w, c)$ counts the number of times that words w and c cooccur within a window of size L in corpus \mathcal{D} , and $\#(w)$, $\#(c)$ counts the number of occurrences of words w and c in \mathcal{D} . $|\mathcal{D}|$ is total

number of word tokens in the corpus. L is typically around 5 to 10; we set $L = 5$ throughout this paper.

The key idea behind both word2vec [21] and GloVe[24] is to find embedding vectors u_w and u_c such that for any w, c combination,

$$u_w^T u_c \approx \text{PMI}(\mathcal{D}, L)_{w,c}$$

where each u_w has length $d \ll V$. While both [21] and [24] offer highly scalable algorithms such as negative sampling to do this implicitly, later work in [15] showed that these are equivalent to low-rank factorization of the $\text{PMI}(\mathcal{D}, L)$ ¹. Our approach is primarily motivated by this observation. We note that though the PMI matrices are of size $V \times V$, in real-world datasets it is typically sparse as observed in [24]. Therefore the factorization can be made efficient.

2.2 Temporal word embeddings

A natural extension of the static word embedding intuition is to use this matrix factorization technique on each time sliced corpus \mathcal{D}_t separately. Specifically, for each time slice t , we define the w, c -th entry of *positive* PMI matrix ($\text{PPMI}(t, L)$) as²

$$\text{PPMI}(t, L)_{w,c} = \max\{\text{PMI}(\mathcal{D}_t, L)_{w,c}, 0\}.$$

The temporal word embeddings $U(t)$'s must satisfy

$$U(t)U(t)^T \approx \text{PPMI}(t, L). \quad (2)$$

One way to find such $U(t)$ is for each t , factorize $\text{PPMI}(t, L)$ using either an eigenvalue method or solving a matrix factorization problem iteratively.

Alignment Imposing (2) is not sufficient for a unique embedding, since the solutions are invariant under rotation; that is, for any $d \times d$ orthogonal matrix R and embedding $\hat{U}(t) = U(t)R$, the approximation error in (2) is the same since

$$\hat{U}(t)\hat{U}(t)^T = U(t)RR^T U(t)^T = U(t)U(t)^T.$$

For this reason, it is important to enforce *alignment*; if word w did not semantically shift from t to $t + 1$, then we additionally require $u_w(t) \approx u_w(t + 1)$.

To do this, [10, 13] propose two-step procedures; first, they factorize each $Y(t)$ separately, and afterwards enforce alignment using local linear mapping [13] or solving an orthogonal procrustes problem [10]. Note that in these methods, aligning $U(t)$ to $U(t')$ assumes that we desire $U(t) \approx U(t')$. If we only pick $t' = t + 1$ (as done in [10]), this assumption is reasonable because between any two years, only a few words experience semantic shift, emergence, or death. However, this becomes problematic if $U(t)$ was a particularly undersampled year; all subsequent year embeddings and previous year embeddings will be poorly aligned.

2.3 Our model

We propose finding temporal word embeddings as the solution of the following joint optimization problem:

$$\min_{U(1), \dots, U(T)} \frac{1}{2} \sum_{t=1}^T \|Y(t) - U(t)U(t)^T\|_F^2 + \frac{\lambda}{2} \sum_{t=1}^T \|U(t)\|_F^2 + \frac{\tau}{2} \sum_{t=2}^T \|U(t-1) - U(t)\|_F^2 \quad (3)$$

where $Y(t) = \text{PPMI}(t, L)$ and $\lambda, \tau > 0$. Here the penalty term $\|U(t)\|_F^2$ enforces the low-rank data-fidelity as widely adopted in previous literature. The key smoothing term $\|U(t-1) - U(t)\|_F^2$ encourages the word embeddings to be aligned. The parameter τ controls how fast we allow the embeddings to change; $\tau = 0$ enforces no alignment, and picking $\tau \rightarrow \infty$ converges to a static embedding with $U(1) = U(2) = \dots = U(T)$. Note that the methods of [10, 13] can be viewed as suboptimal solutions of (3), in that they optimize for each term separately. For one, while the strategies in [13] and [10] enforce alignment pairwise, we enforce alignment across *all* time slices; that is, the final aligned solution $U(t)$ is influenced by not only $U(t-1)$ and $U(t+1)$, but every other embedding as well. This avoids the propagation of alignment errors caused by a specific time frame's subsampling. Additionally, consider an extreme case in which word w is absent from \mathcal{D}_t but has similar meaning in both $t-1$ and $t+1$. Directly applying any matrix factorization technique to each time point would enforce $u_w(t) \approx 0$. However, for the right choice of τ , the solution $u_w(t)$ to (3) will be close to $u_w(t-1)$ and $u_w(t+1)$. Overall, our embeddings are able to achieve high fidelity embeddings with a much smaller corpus, and in particular, in section 6, we demonstrate that our embeddings are robust against sudden undersampling of specific time slices.

3 OPTIMIZATION

A key challenge in solving (3) is that for large V and T , one cannot fit all the PPMI matrices $Y(1), \dots, Y(T)$ in memory, even though $Y(t)$ is sparse. Therefore, for scalability, an obvious solution is to first decompose by each $U(t)$, using alternating minimization to solve at each step

$$\min_{U(t)} \overbrace{\frac{1}{2} \|Y(t) - U(t)U(t)^T\|_F^2}^{f(U(t))} + \frac{\lambda}{2} \|U(t)\|_F^2 + \frac{\tau}{2} (\|U(t-1) - U(t)\|_F^2 + \|U(t) - U(t+1)\|_F^2) \quad (4)$$

for a specific t . Solving (4) can be done using any fast first-order method, such as gradient descent. The gradient of the first term alone is given by

$$\nabla f(U(t)) = -2Y(t)U(t) + 2U(t)U(t)^T U(t) \quad (5)$$

We see that minimizing for each $U(t)$ requires a sequence of gradient computations, each of order $O(\text{nnz}(Y(t))d + d^2V)$ ³ (which is then nested in iteratively minimizing $U(t)$ for each t). In practical applications, V is in the order of tens to hundreds of thousands, and T is in the order of tens to hundreds.

³where $\text{nnz}(\cdot)$ is the number of nonzeros in the matrix.

¹with a constant shift that can be zero.

²We consider the PPMI rather than the PMI because when $\frac{\#(w,c) \cdot |\mathcal{D}|}{\#(w) \cdot \#(c)}$ is very small, taking the log results in large negative values and is thus extremely unstable. Since for most significantly related pairs w and c the log argument is > 1 , thresholding it in this way will not affect the solution significantly, but will offer much better numerical stability. This approach is not unique to us; [15] also factorize the PPMI .

Let us instead look at a slightly relaxed problem of minimizing

$$\min_{U(1), V(1), \dots} \frac{1}{2} \sum_{t=1}^T \|Y(t) - U(t)W(t)^T\|_F^2 + \frac{\gamma}{2} \sum_{t=1}^T \|U(t) - W(t)\|_F^2 \quad (6)$$

$$+ \frac{\lambda}{2} \sum_{t=1}^T \|U(t)\|_F^2 + \frac{\tau}{2} \sum_{t=2}^T \|U(t-1) - U(t)\|_F^2$$

$$+ \frac{\lambda}{2} \sum_{t=1}^T \|W(t)\|_F^2 + \frac{\tau}{2} \sum_{t=2}^T \|W(t-1) - W(t)\|_F^2$$

where variables $W(t), t = 1, \dots, T$ are introduced to break the symmetry of factorizing $Y(t)$. Now, minimizing each $U(t)$ (and equivalently with $W(t)$) is just the solution of a ridge regression problem, and can be solved by setting the gradient of the objective of (6) to 0, i.e. $U(t)A = B$ where

$$A = W(t)^T W(t) + (\gamma + \lambda + 2\tau)I,$$

$$B = Y(t)W(t) - \gamma W + \tau(U(t-1) + \tau U(t+1))$$

for $t = 2, \dots, T-1$, and constants adjusted for $t = 0, T$. Note that this can be further decomposed to row-by-row blocks, by minimizing over a row of $U(t)$ at a time. This allows scaling for very large V , as only a row of $Y(t)$ must be loaded at a time.

Block coordinate descent vs. stochastic gradient descent : The method described here is more commonly referred to as *block coordinate descent (BCD)* because it minimizes with respect to a single block ($U(t)$ or $W(t)$) at a time, and the block size can be made even smaller (a few rows of $U(t)$ or $W(t)$) to maintain scalability. The main appeal of BCD is scalability [33]; however, a main drawback is lack of convergence guarantees, even in the case of convex optimization [26]. In practice, however, BCD is highly successful and has been used in many applications (see [32] for examples). Another choice of optimization is stochastic gradient descent (SGD), which decomposes the *objective* as a sum of smaller terms. For example, the first term of (6) can be written as a sum of terms, each using only one row of $Y(t)$:

$$f(U(t)) = \sum_{i=1}^V \|Y(t)[i, :] - u_i(t)^T W(t)\|_2^2.$$

The complexity at first glance is smaller than that of BCD; however, SGD comes with the well-documented issues of slow progress and hard-to-tune step sizes, and in practice, can be much slower. However, we point out that the choice of the optimization method is agnostic to our model; anything that successfully solves (3) should lead to an equally successful embedding.

4 EXPERIMENTAL DATASET AND SETUP

In this section we describe the specific procedure to generate embeddings for the next two evaluation sections.

News article dataset: The following is how we compute our PPMI matrices, which are then used to construct both our embedding and those we compare against. First, we crawl a total of 99,872 articles from the New York Times, published between 1990 and 2016. In addition to a main body, each article contains several metadata fields, such as title, author, release date, and section label (e.g., Business, Sports); in total, there are 59 news sections. We use yearly time slices, dividing the corpus into $T = 27$ partitions. After removing rare words (fewer than 200 occurrences in all articles)

and stop words, our vocabulary is in total $V = 20,936$ unique words. The co-occurrences are computed for each time slice t with a window size $L = 5$.

Training details for our embedding: After some parameter search and visual inspection, we set $\lambda = 10$, $\tau = \gamma = 50$, and run for 5 iterations. (Interestingly, setting $\lambda = 0$ also yielded good results, but required more iterations to converge.) The block variable is one matrix ($U(t)$ or $V(t)$ for a specific t).

Distance metric: All distances between words are calculated as the cosine similarity between embeddings.

$$\text{similarity}(a, b) = \text{cosine}(u_a, u_b) = \frac{u_a^T u_b}{\|u_a\|_2 \cdot \|u_b\|_2}, \quad (7)$$

where u_a and u_b are the embeddings of words a and b .

5 QUALITATIVE EVALUATION

Our temporal word embeddings illuminate interesting news features in a number of ways. We explore a few here: using vector norms to determine concept popularity represented by words, observing semantically shifting trajectories to identify the emergence of companies and famous people, and exploiting the alignment to find equivalent roles of people in different time periods.

5.1 Popularity determination

It has often been observed that word embeddings computed by factorizing PMI matrices have norms that grow with word frequency [1, 24]. These word vector norms can be viewed as a time series for detecting the trending concepts (e.g., sudden semantic shifts or emergences) behind words, with more robustness than word frequency.

Figures 1 and 2 illustrate the comparison between embedding norm and frequency for determining *concept* popularity per year, determined by key words in the New York Times corpus. Generally, comparing to frequencies which are much more sporadic and noisy, we note that the norm of our embeddings encourages smoothness and normalization while preserving the impact periods. In Figure 1, the embedding norms display nearly even 4-year humps corresponding to each president's term. In every term, the name of each current president becomes a trending concept which plays an important role in the information structure at the time. Two interesting observations can be gleaned. First, since Hillary Clinton continuously served as Secretary of State during 2009-2013, the popularity of `clinton` was preserved; however it was still not as popular as `president obama`. Second, because of the presidential campaign, `trump` in 2016 has a rising popularity that greatly surpasses that of his former role as a business man, and eventually surpasses his opponent `clinton` in terms of news coverage. In Figure 2, we can see smooth rises and falls of temporary phenomena (the `enron` scandal and `qaeda` rises). Although their frequencies drop sharply after the peak, their trends of impact should still exist for a while as they really did. For the basketball star `pippen`, although his publicity (e.g., frequency) was relatively fewer than business terms, his popularity is still recognized by the enhancement in vector norm. For another term `isis`, we can see that it replaced `qaeda` as the trending terrorist organization in news media.

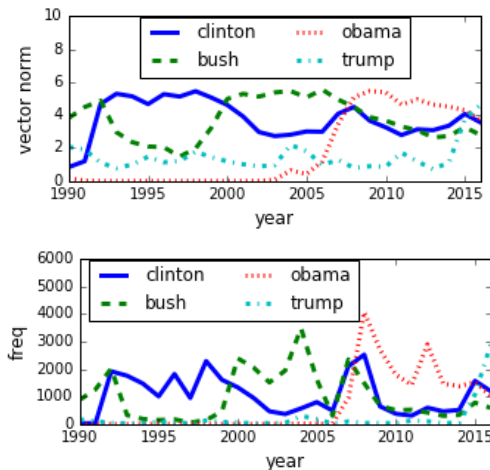


Figure 1: Norm (top) and relative frequency (bottom) throughout years 1990-2016. We select the names of U.S presidents within this time frame - clinton, bush, obama, and trump. We note that bush could refer to George H. W. Bush (1989-1993) or George W. Bush (2001-2009). Clinton could refer to Bill Clinton (1993-2001) or Hillary Clinton (U.S. secretary of states in 2009-2013 and U.S. presidential candidate in 2014-2016).

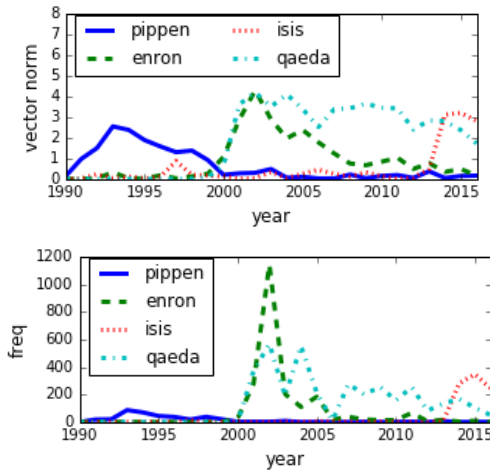


Figure 2: Norm (top) and relative frequency per year in corpus (bottom) of major event keyword: pippen for basketball stardom, enron for corporation scandal, qaeda and isis for emerging terrorism groups.

5.2 Trajectory visualization

As new concepts and information appear over time, words are dominated by different meanings. Visualizing trajectories of word meanings can enable broad applications, such as characterizing brands and persons, and analyzing emerging meanings. Figure 3 shows the trajectory of each word of interest w . We plot the 2-D t-SNE projection of each word’s temporal embeddings across time as its trajectory. We also plot the closest words for each temporal state. We picked four words of interest: apple and amazon

as emerging brand names, and obama and trump as people with changing professional roles.

In all cases, the embeddings illustrate significant semantic shifts of the words of interest during this 27-year time frame. We see apple shift from a fruit and dessert ingredient to the electronic corporation. Interestingly, there is a spike in 1994, when Apple led a short tide of discussion because of the replacement of the CEO and a collaboration with IBM, then went back to decline until the recovery by Steve Jobs around 2000. Similarly, amazon shifts from a forest to an e-commerce company, finally landing in 2016 as a TV content distributor. The president names, obama and trump, are most telling, shifting from their pre-presidential lives (Obama as a university lecturer and Trump as a real-estate developer and TV celebrity) to the political sphere. These visualizations show two points: first, our temporal word embeddings can well capture the semantic shifts of words across time, and second, our model provides high alignment quality in that same-meaning words across different years have geometrically close embeddings.

5.3 Equivalence searching

Another key advantage of word alignment is the ability to find “equivalent” items or people over time. We first show examples with technology, then official roles, and finally sports titles. In this type of test, we create a query consisting of a word-year pair that is particularly representative of that technology in that year, and look for other word-year pairs in its vicinity, across years.

Table 1 lists the closest words (*top-1*) to the temporal vector of technological items over the time periods, where we lump semantically similar words together. For example, the first column shows that iphone in 2012 is closely associated with smartphones in recent years, but is close to words such as desktop and macintosh in the 90’s; interestingly, telephone never appears, suggesting the iPhone serves people more as a portable computer than a calling device. As another example, by looking at the trajectory of twitter, we see the evolution of news sources, from TV & radio news broadcasts in the 90s to chatrooms, websites, and emails in the early 2000s, blogs in the late 2000s, and finally tweets today. Again, interestingly, letters or telegrams never appear, suggesting twitter is more of a news source than a communication device. The last example is less controversial; mp3 represents the main form of which music is consumed in 2000, replacing disk and stereo in 1990s (cassette also appears in *top-3*) and is later replaced by online streaming. We can see a one-year spike of Napster which was shut down because of copyright infringement⁴, and later a new legal streaming service - iTunes which is operated by Apple.

Next, we use embeddings to identify people in political roles. Table 2 attempts to discover who is the U.S. president⁵ and New York City mayor⁶ of the time, using as query obama in 2016 and blasio in 2015. For president, only the closest word is listed, and is always correct. For mayor, the first word is given unless it is mayor, and then the second word is given. We can see that both

⁴Napster ended its streaming service in 2001, so our equivalence is captured 2 years late; this delay could be because though the event happened in 2001, the legal ramifications were analyzed heavily in subsequent years.

⁵All data was scraped about half a year before Donald Trump was elected.

⁶We intentionally choose New York City because it is the most heavily discussed city in the New York Times.

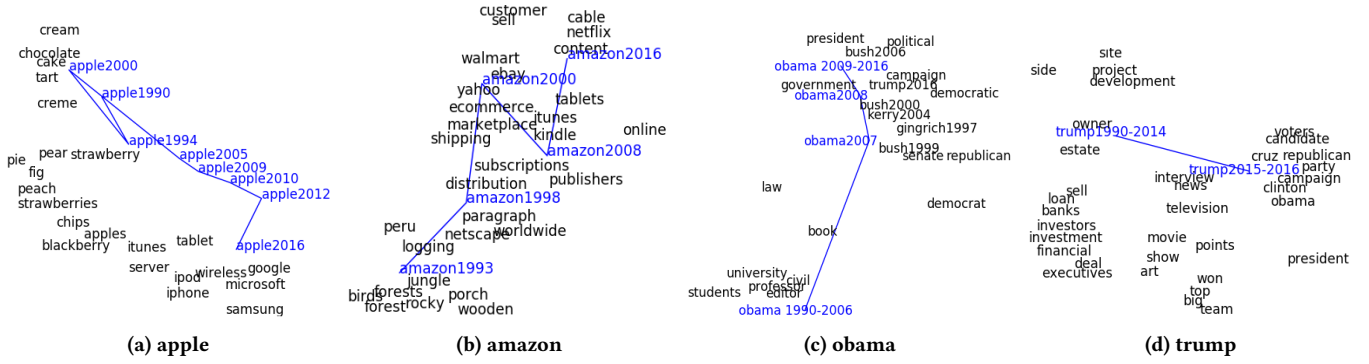


Figure 3: Trajectories of brand names and people through time: apple, amazon, obama, and trump.

Table 1: Equivalent technologies through time: iphone, twitter, and mp3.

Query	iphone, 2012	twitter, 2012	mp3, 2000
90-94	desktop, pc, dos, macintosh, software	broadcast, cnn, bulletin, tv, radio, messages, correspondents	stereo, disk, disks, audio
95-96			mp3
97			
98-02	pc	chat, messages, emails, web	napster
03			mp3
04			
05-06	ipod	blog, posted	itunes, downloaded
07-08	iphone		
09-12		twitter	
13-16	smartphone, iphone		

Table 2: “Who governed?” The closest word to obama at year 2016 (role as president of United State) and blasio at year 2015 (role as mayor of New York City (NYC)). The stars indicates incorrect answers.

Question	US president	NYC mayor
Query	obama, 2016	blasio 2015
90-92	bush	dinkins
93	clinton	
94-00		giuliani
01		
02-05	bush	bloomberg
06		n/a*
07		
08		bloomberg
09-10	obama	cuomo*
11		bloomberg
12		blasio
13-16		

the roles of US president and NYC major have been well searched for different persons in their terms of service. In 2011, since cuomo was the governor of NY state, it is also partially relevant.

Finally, we search for equivalences in sports, repeating the experiment for the ATP rank 1 male tennis player as shown in Table

Table 3: “Who was the ATP No.1 ranked male player?” The closest word to nadal at year 2010 for each year is listed. The correct answer is based on ATP year-end ranking and are bolded in the table.

year	1990	1991	1992	1993
word	edberg	lendl	sampras	sampras
1994	1995	1996	1997	1998
sampras	sampras	ivanisevic	sampras	sampras
1999	2000	2001	2002	2003
sampras	sampras	agassi	capriati	roddick
2004	2005	2006	2007	2008
federer	federer	roddick	federer	nadal
2009	2010	2011	2012	2013
federer	nadal	djokovic	federer	federer
2014	2015			
federer	djokovic			

3. In the case of president and mayor, we are heavily assisted by the fact that they are commonly referred to by a title: “President Obama” and “Mayor de Blasio”. Tennis champions, on the other hand, are not referred by titles. Still, a surprising number of correct champions appear as closest words, and all the names are those of famous tennis players. A more exhaustive empirical study of alignment quality is provided in section 6.

6 QUANTITATIVE EVALUATION

In this section, we empirically evaluate our proposed Dynamic Word2Vec model (DW2V) against other temporal word embedding methods. In all cases, we set the embedding dimension to $d = 50$. We have the following baselines:

- **Static-Word2Vec (SW2V)**: the standard word2vec embeddings [22] trained on the entire corpus ignoring time information.
- **Transformed-Word2Vec (TW2V)** [13]: the embeddings $U(t)$ are first trained separately by factorizing PPMI matrix for each year t , and then transformed by optimizing a linear transformation matrix which minimizes the distance between $u_w(t)$ and $u_w(t')$ for the $k = 30$ nearest words’ embeddings to the querying word w .

- **Aligned-Word2Vec (AW2V) [10]:** the embeddings $U(t)$ are first trained by factorizing the PPMI matrix for each year t , and then aligned by searching for the best orthonormal transformation between $U(t)$ and $U(t + 1)$.

6.1 Semantic similarity

One of the most important properties of a word embedding is how accurately it carries the meaning of words. Therefore, we develop a test to see if words can be categorized by meaning based on embeddings. In analyzing news media, one method to gather temporal word meanings is to find its yearly frequency of usage in article sections (e.g., *Business*, *Sports*). It is important to note that this information is not used in the word embedding learning. For example, we see that *amazon* occurs 41% of the time in *World* in 1995, associating strongly with forestry, and 50% of the time in *Technology* in 2012, associating strongly with e-commerce. We thus use this to establish a ground truth of word category, by identifying words in years that are exceptionally numerous in one particular news section. Specifically, we select the 11 most popular and discriminative sections of the New York Times⁷, and for each section s and each word w in year t , we compute its percentage p of occurrences in each section. For avoiding duplicated word-time-section $\langle w, t, s \rangle$ triplets, for a particular w and s we only keep the year of the largest strength, and additionally filter away any triplet with strength less than $p = 35\%$. To limit the size differences among categories, for every section s with more than 200 qualified triplets, we keep the *top-200* words by strength. In total, this results in 1888 triplets across 11 sections, where every word-year pair is strongly associated with a section as its true category.

We then apply spherical K-means, which uses cosine similarity between embeddings as the distance function for clustering, with $K = 10, 15$, and 20 clusters. We use two metrics to evaluate the clustering results.

- **Normalized Mutual Information (NMI)**, defined as

$$NMI(L, C) = \frac{I(L; C)}{[H(L) + H(C)]/2}, \quad (8)$$

where L represents the set of labels and C the set of clusters. $I(L; C)$ denotes the sum of mutual information between any cluster c_i and any label l_j , and $H(L)$ and $H(C)$ the entropy for labels and clusters, respectively. This metric evaluates the purity of clustering results from an information-theoretic perspective.

- **F_β -measure (F_β)**, defined as

$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}, \quad (9)$$

where $P = \frac{TP}{TP+FP}$ denotes the precision and $R = \frac{TP}{TP+FN}$ denotes the recall. (TP/FP = true/false positive, TN/FN = true/false negative.) As an alternative method to evaluate clustering, we can view every pair of words as a series of decisions. Pick any two (w, t) pairs. If they are clustered together and additionally have the same section label, this is a correct decision; otherwise, the clustering performed a wrong decision. The metric F_β measures accuracy as the (β -weighted) harmonic mean of the

Table 4: Normalized Mutual Information (NMI).

Method	10 Clusters	15 Clusters	20 Clusters
SW2V	0.6736	0.6867	0.6713
TW2V	0.5175	0.5221	0.5130
AW2V	0.6580	0.6618	0.6386
DW2V	0.7175	0.7162	0.6906

Table 5: F-measure (F_β).

Method	10 Clusters	15 Clusters	20 Clusters
SW2V	0.6163	0.7147	0.7214
TW2V	0.4584	0.5072	0.5373
AW2V	0.6530	0.7115	0.7187
DW2V	0.6949	0.7515	0.7585

precision and recall. We set $\beta = 5$ to give more weight to recall by penalizing false negative more strongly.

Tables 4 and 5 show the clustering evaluation. We can see that our proposed DW2V consistently outperforms other baselines for all values of K . These results show two advantages. First, the word semantic shift has been captured by the temporal embeddings (for example, by correlating correctly with the section label of *amazon*, which changes from *World* to *Technology*). Second, since embeddings of words of all years are used for clustering, a good clustering result indicates good alignment across years. We can also see that AW2V also performs well, as it also applies alignment between adjacent time slices for all words. However, TW2V does not perform well as others, suggesting that aligning locally (only a few well-picked words) is not sufficient for high alignment quality.

6.2 Alignment quality

We now more directly evaluate alignment quality, i.e. the property that the semantic distribution in temporal embedding space should be consistent over time. For example, if a word such as *estate* or *republican* does not change much throughout time, its embedding should remain relatively constant for different t . By the same logic, if a word such as *trump* does change association throughout time, its embedding should reflect this shift by moving from one position to another (e.g., *estate* \rightarrow *republican*). We saw this in the previous section for static words like *president* or *mayor*; they do not change meanings, though they are accompanied by names that shift to them every few years.

To examine the quality of embedding alignment, we create a task to query equivalences across years. For example, given *obama-2012*, we want to query its equivalent word in 2002. As we know *obama* is the U.S. president in 2012; its equivalent in 2002 is *bush*, who was the U.S. president at that time. In this way, we create **two testsets**. The first one is based on publicly recorded knowledge that for each year lists different names for a particular role, such as U.S. president, U.K. prime minister, NFL superbowl champion team, and so on. For each year (e.g., 2012), we put its word (e.g., *obama*) into the embedding set of every other year for query its equivalence in top closest words. The second test is human-generated, for exploring more interesting concepts like emerging technologies, brands and major events (e.g., disease outbreaks and financial crisis). For constructing the test word pairs, we first select emerging terms which have not been popularized before 1994, then query their well known precedents during 1990 to 1994 (e.g., *app-2012* can

⁷Arts, Business, Fashion & Style, Health, Home & Garden, Real Estate, Science, Sports, Technology, U.S., World.

Table 6: Mean Reciprocal Rank (MRR) and Mean Precision (MP) for Testset 1.

Method	MRR	MP@1	MP@3	MP@5	MP@10
SW2V	0.3560	0.2664	0.4210	0.4774	0.5612
TW2V	0.0920	0.0500	0.1168	0.1482	0.1910
AW2V	0.1582	0.1066	0.1814	0.2241	0.2953
DW2V	0.4222	0.3306	0.4854	0.5488	0.6191

Table 7: Mean Reciprocal Rank (MRR) and Mean Precision (MP) for Testset 2.

Method	MRR	MP@1	MP@3	MP@5	MP@10
SW2V	0.0472	0.0000	0.0787	0.0787	0.2022
TW2V	0.0664	0.0404	0.0764	0.0989	0.1438
AW2V	0.0500	0.0225	0.0517	0.0787	0.1416
DW2V	0.1444	0.0764	0.1596	0.2202	0.3820

correspond to software-1990). For emerging word (e.g., app) we extract its popularized year (e.g., 2012) with maximum frequency, and put its embedding into each year from 1990 to 1994 for query its precedent (e.g., software). Each word-year pair now forms a query and an answer; in total we have $N = 11028$ such pairs in the first testset, and $N = 445$ in the second one.

We use two metrics to evaluate the performance.

- For each test i , the correct answer word is identified at position $\text{rank}[i]$ for closest words. The *Mean Reciprocal Rank (MRR)* is defined as

$$MRR = \frac{1}{N} \sum_{i=1}^N \frac{1}{\text{rank}[i]}, \quad (10)$$

where $\frac{1}{\text{rank}[i]} = 0$ if the correct answer is not found in the *top-10*. Higher MRR means that correct answers appear more closely and unambiguously with the query embedding.

- Additionally, for test i consisting of a query and target word-year pair, consider the closest K words to the query embedding in the target year. If the target word is among these K words, then the *Precision@K* for test i (denoted $P@K[i]$) is 1; else, it is 0. Then the *Mean Precision@K* is defined as

$$MP@K = \frac{1}{N} \sum_{i=1}^N (P@K[i]). \quad (11)$$

Higher precision indicates a better ability to acquire correct answers using close embeddings.

Table 6 and 7 show the evaluation of the alignment test. We can see that our proposed method outperforms others and shows good alignment quality. Comparing testset 1 and testset 2, the first one has a large amount of queries with many short range alignments (e.g., 2012 to 2013) while the second one has smaller query volume and mostly consists of long range alignments (e.g., 2012 to 1990). In baselines, SW2V performs relatively well in testset 1 since semantic distribution does not change much in short ranges which makes this test favorable to static embeddings. However, SW2V degrades sharply in testset 2, where the long range alignment is more needed. For TW2V, since it does an individual year-to-year (e.g., 2012-to-1990) transformation by assuming that the local structure of target words does not shift, its overall alignment quality of whole embedding sets is not satisfied in testset 1 which contains large volume of queries. However, it does similarly to AW2V in testset 2 because

Table 8: MRR and MP for Alignment with every 3 years sub-sampled.

Method	r	MRR	MP@1	MP@3	MP@5	MP@10
AW2V	100%	0.1582	0.1066	0.1814	0.2241	0.2953
AW2V	10%	0.0884	0.0567	0.1020	0.1287	0.1727
AW2V	1%	0.0409	0.0255	0.0475	0.0605	0.0818
AW2V	0.1%	0.0362	0.0239	0.0416	0.0532	0.0690
DW2V	100%	0.4222	0.3306	0.4854	0.5488	0.6191
DW2V	10%	0.4394	0.3489	0.5036	0.5628	0.6292
DW2V	1%	0.4418	0.3522	0.5024	0.5636	0.6310
DW2V	0.1%	0.4427	0.3550	0.5006	0.5612	0.6299

its individual year-to-year transformation makes it more capable for long range alignment and fewer query testset. AW2V, which enforces alignment for whole embedding sets between adjacent time slices, provides quite reliable performance. However, its alignment quality is not as good as ours, suggesting that their two-step approach is not as successful in enforcing global alignment.

6.3 Robustness

Finally, we explore the robustness of our embedding against subsampling for select years. Table 8 shows the result of the alignment task (testset 1) for vectors computed from subsampled co-occurrence matrices for every three years from 1991 to 2015. To subsample, each element C_{ij} is replaced with a randomly drawn integer \hat{C}_{ij} from a Binomial distribution for rate r and $n = C_{ij}$ trials; this simulates the number of co-occurrences measured if they had been missed with probability r . The new frequency \hat{f} is then renormalized so that $\hat{f}_i/f_i = \sum_j \hat{C}_{ij}/\sum_j C_{ij}$. Listed are the alignment test results for $r = 1, 0.1, 0.01$, and 0.001 compared against [10], which otherwise performs comparably with our embedding. Unsurprisingly, for extreme attacks (leaving only 1% or 0.1% cooccurrences), the performance of [10] degrades sharply; however, because of our joint optimization approach, the performance of our embeddings seems to hold steady.

7 RELATED WORK

Word embedding learning: The idea of word embeddings has existed at least since 90s, with vectors computed as rows of the cooccurrence [18], through matrix factorization [7], and most famously through deep neural networks [4, 6]. They have recently been repopularized with the success of low-dimensional embeddings like GloVe [24] and word2vec [21, 22], which have been shown to greatly improve the performance in key NLP tasks, like document clustering [14], LDA [25], and word similarity [2, 16], and have surprising qualitative results, like man - woman + queen \approx king. There is a close connection between these recent methods and our proposed method, in that both word2vec and GloVe have been shown to be equivalent to matrix factorization of a shifted PMI matrix [15].

Temporal word embeddings and evaluations: While NLP tools have been used frequently to discover emerging word meanings and societal trends, many of them rely on changes in the cooccurrence or PMI matrix [9, 11, 19, 23, 31], changes in parts of speech, [20] or other statistical methods [3, 13, 28]. A few works use low-dimensional word embeddings, but either do no smoothing [27], or two-step methods: [12] “smooths” by using the current year’s

embedding as the word2vec initialization of the next year’s embedding; [10] solves Procrustes problems to find orthogonal alignment matrices between adjacent years; and [13] solves a least squares problem to find a similar linear transformation. Semantic shift and emergences are also evaluated in many different ways. In [27], word shifts are identified by tracking the mean angle between a word and its neighbors. One of the several tests in [13] create synthetic data with injected semantic shifts, and quantifies the accuracy of capturing them using various time series metrics. In [20], the authors show the semantic meaningfulness of key lexical features by using them to predict the time stamp of a particular phrase. And, [23] makes the connection that emergent meanings usually coexist with previous meanings, and use dynamic embeddings to discover and identify multisenses, evaluated against WordNet. Primarily, temporal word embeddings are evaluated against human-created databases of known semantically shifted words [10, 13, 28] which is our approach as well.

8 CONCLUSIONS

We studied the evolving word semantics as a dynamic word embedding learning problem. We proposed a model to learn time-aware word embedding and use it to dynamically mine text corpora. Our proposed method learns both the embedding and aligns them across time simultaneously, and has several benefits: higher interpretability for embeddings, better quality with less data, and more reliable alignment quality for across-time querying. We solve the resulting optimization using a block coordinate descent method. We designed qualitative and quantitative methods to evaluate temporal embeddings for evolving word semantics.

REFERENCES

- [1] Sanjeev Arora, Yuanzhi Li, Yingyu Liang, Tengyu Ma, and Andrej Risteski. 2015. Rand-walk: A latent variable model approach to word embeddings. *arXiv preprint arXiv:1502.03520* (2015).
- [2] Marco Baroni, Georgiana Dinu, and Germán Kruszewski. 2014. Don’t count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors. In *ACL (1)*. 238–247.
- [3] Pierpaolo Basile, Annalina Caputo, and Giovanni Semeraro. 2014. Analysing word meaning over time by exploiting temporal random indexing. In *First Italian Conference on Computational Linguistics CLiC-it*.
- [4] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A Neural Probabilistic Language Model. *Journal of Machine Learning Research* 3 (2003), 1137–1155.
- [5] David M Blei and John D Lafferty. 2006. Dynamic topic models. In *Proceedings of the 23rd international conference on Machine learning*. ACM, 113–120.
- [6] Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *Proceedings of the 25th international conference on Machine learning*. ACM, 160–167.
- [7] Scott Deerwester, Susan T Dumais, George W Furnas, Thomas K Landauer, and Richard Harshman. 1990. Indexing by latent semantic analysis. *Journal of the American society for information science* 41, 6 (1990), 391.
- [8] John R Firth. 1957. {A synopsis of linguistic theory, 1930-1955}. (1957).
- [9] Kristina Gulordava and Marco Baroni. 2011. A distributional similarity approach to the detection of semantic change in the Google Books Ngram corpus. In *Proceedings of the GEMS 2011 Workshop on GEometrical Models of Natural Language Semantics*. Association for Computational Linguistics, 67–71.
- [10] William L Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change. *arXiv preprint arXiv:1605.09096* (2016).
- [11] Gerhard Heyer, Florian Holz, and Sven Teresniak. 2009. Change of Topics over Time-Tracking Topics by their Change of Meaning. *KDIR* 9 (2009), 223–228.
- [12] Yoon Kim, Yi-I Chiu, Kentaro Hanaki, Darshan Hegde, and Slav Petrov. 2014. Temporal analysis of language through neural language models. *arXiv preprint arXiv:1405.3515* (2014).
- [13] Vivek Kulkarni, Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2015. Statistically significant detection of linguistic change. In *Proceedings of the 24th International Conference on World Wide Web*. ACM, 625–635.
- [14] Matt J Kusner, Yu Sun, Nicholas I Kolkin, Kilian Q Weinberger, and others. 2015. From Word Embeddings To Document Distances. In *ICML*, Vol. 15, 957–966.
- [15] Omer Levy and Yoav Goldberg. 2014. Neural word embedding as implicit matrix factorization. In *Advances in neural information processing systems*. 2177–2185.
- [16] Omer Levy, Yoav Goldberg, and Ido Dagan. 2015. Improving distributional similarity with lessons learned from word embeddings. *Transactions of the Association for Computational Linguistics* 3 (2015), 211–225.
- [17] Xuanyi Liao and Guang Cheng. 2016. Analysing the Semantic Change Based on Word Embedding. In *International Conference on Computer Processing of Oriental Languages*. Springer, 213–223.
- [18] Kevin Lund and Curt Burgess. 1996. Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers* 28, 2 (1996), 203–208.
- [19] Jean-Baptiste Michel, Yuan Kui Shen, Aviva Presser Aiden, Adrian Veres, Matthew K Gray, Joseph P Pickett, Dale Hoiberg, Dan Clancy, Peter Norvig, Jon Orwant, and others. 2011. Quantitative analysis of culture using millions of digitized books. *science* 331, 6014 (2011), 176–182.
- [20] Rada Mihalcea and Vivi Nastase. 2012. Word epoch disambiguation: Finding how words change over time. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2*. Association for Computational Linguistics, 259–263.
- [21] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781* (2013).
- [22] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*. 3111–3119.
- [23] Sunny Mitra, Ritwik Mitra, Martin Riedl, Chris Biemann, Animesh Mukherjee, and Pawan Goyal. 2014. That’s sick dude!: Automatic identification of word sense change across different timescales. *arXiv preprint arXiv:1405.4392* (2014).
- [24] Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global Vectors for Word Representation. In *EMNLP*, Vol. 14, 1532–1543.
- [25] James Petterson, Wray Buntine, Shrawan M Narayanamurthy, Tibério S Caetano, and Alex J Smola. 2010. Word features for latent dirichlet allocation. In *Advances in Neural Information Processing Systems*. 1921–1929.
- [26] Michael JD Powell. 1973. On search directions for minimization algorithms. *Mathematical Programming* 4, 1 (1973), 193–201.
- [27] Eyal Sagi, Stefan Kaufmann, and Brady Clark. 2011. Tracing semantic change with latent semantic analysis. *Current methods in historical semantics* (2011), 161–183.
- [28] Xuri Tang, Weiguang Qu, and Xiaohe Chen. 2016. Semantic change computation: A successive approach. *World Wide Web* 19, 3 (2016), 375–415.
- [29] Chong Wang, David Blei, and David Heckerman. 2012. Continuous time dynamic topic models. *arXiv preprint arXiv:1206.3298* (2012).
- [30] Xuerui Wang and Andrew McCallum. 2006. Topics over time: a non-Markov continuous-time model of topical trends. In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 424–433.
- [31] Derry Tanti Wijaya and Reyyan Yeniterzi. 2011. Understanding semantic change of words over centuries. In *Proceedings of the 2011 international workshop on DETecting and Exploiting Cultural diversity on the social web*. ACM, 35–40.
- [32] Stephen J Wright. 2015. Coordinate descent algorithms. *Mathematical Programming* 151, 1 (2015), 3–34.
- [33] Hsiang-Fu Yu, Cho-Jui Hsieh, Si Si, and Inderjit Dhillon. 2012. Scalable coordinate descent approaches to parallel matrix factorization for recommender systems. In *Data Mining (ICDM), 2012 IEEE 12th International Conference on*. IEEE, 765–774.
- [34] Yating Zhang, Adam Jatowt, Sourav S Bhowmick, and Katsumi Tanaka. 2016. The Past is Not a Foreign Country: Detecting Semantically Similar Terms across Time. *IEEE Transactions on Knowledge and Data Engineering* 28, 10 (2016), 2793–2807.